Appendix A: Match Type

Determining the match type of a keyword is a basic but important task for the advertisers. The match type affects the size of the possible audience that a keyword can reach. Both Google and Bing offer five match types – broad match, broad match modifier, phrase match, exact match and negative match[1].

Table A-1 shows the examples of the same keyword “women’s jewelry” with all but negative match types. Broad match allows for misspellings, synonyms and relevant variations of the term. For example, search queries like “buy ladies jewelry” could trigger the search ads on keyword “women’s jewelry” with broad match. The exact match only allows close variation of the exact term “women’s jewelry”, while phrase match allows one or more words before or after (not in the middle of) that exact term, such as “buy women’s jewelry”. The broad match modifier is a match type that combines the broad and exact match. An advertiser can use the broad match modifier to specify a term which (or the close variation of which) must be contained in the search queries, but the order of the terms could vary, such as “jewelry for women”. The negative match means that the search queries should not contain the keyword, which can help the advertiser avoid wasting investment on the audience with certain search queries.

Table A-1 Examples for Different Match Types

Match Type	Example search queries that can trigger “women’s jewelry”	Example search queries that cannot trigger “women’s jewelry”
Broad match	*buy ladies jewelry, women’s necklace jewelry, women's jewelry*	*Women’s, jewelry*
Exact match	*women's jewelry*	*Ladies jewelry, women’s necklace, jewelry women’s*
Phrase match	*buy women's jewelry, women's jewelry*	*Women’s necklace, jewelry women’s*
Broad match modifier	*jewelry for women, women's jewelry*	*Women’s necklace, jewelry women’s*

[1] Based on Google AdWords Help document online: https://support.google.com/adwords/answer/2497836?hl=en, and Bing ads training document online: http://advertise.bingads.microsoft.com/en-us/cl/246/training/keyword-match-options. Last Accessed on April 7, 2014.

The focal advertiser runs search campaigns with three different match types -broad, exact, and phrase. In the model, the 505 keyword are from both search engines and include all three match types. To examine the influence of match type on the results and remove the noise due to the mismatch between the customer's search queries and the advertiser's keyword while using the broad match type, we add two dummy variables to equation (1) through (5) for the exact and phrase match types, respectively, to distinguish them from the broad match type which is used as the benchmark match type. The results are shown in Table A-2 to Table A-6. Most coefficient estimates remain the same signs as those in Table 3-7 when significant, with a few exceptions such as : $Google_i$ turns positive and significant in equation (2) which implies that the bid on the same keyword is higher at Google than at Bing due to the more intense competition at Google; $Brand_i$ turns positive and significant in equation (4), indicating a branded keyword has higher click-through rate; and $Specificity_i$ and $Specificity_i^2$ turn positive and significant in equation (4), the magnitude of which, however, is marginal with respect to the overall click-through rate.

In equation (1), the impact of first-click is still negative, especially for the more specific keywords. The coefficients of both $Exact_i$ and $Phrase_i$ are not significant, implying that the keyword match type has no impact on its revenue. However, these coefficients are negative when significant in both equation (2) and (3), indicating that the bid on exact- and phrase-matched keywords is lower than broad-matched keywords while their ad positions are higher. The findings in both equations (2) and (3) are intuitive, because exact and phrase match types can narrow down the range of competing keywords and thus reduce the cost. The advertisers can thus gain the same or even better positions among the search results with a lower bid. In equation (4) and (5), the coefficients of $Exact_i$ are positive when significant, indicating that better matched search with exact-matched keywords leads to higher click-through rates and higher conversions rates. However, phrased-matched keywords only increase the click-through rates but not the conversion rates. Overall, these coefficient estimates are very close to those presented in Table 3-7 in the main text. Since the AIC and BIC are both higher for the model system with these match type dummies (AIC=973,882 and BIC=974,359 for the model with match types versus AIC=889,152 and BIC=889721 for the proposed model in main text), we only discuss the results based on the parsimonious model without match types in the main text.

Table A-2 Coefficient Estimates from Revenue Model

	Estimates	Std. Error	
Intercept	-7.844	2.676	**
$\ln(\text{Impression}_{it})$	0.381	0.034	***
CTR_{it}	0.109	0.020	***
CONV_{it}	1.057	0.310	***
Specificity_i	0.035	0.016	*
$\text{Sq}(\text{Specificity}_i)$	0.005	0.011	
FC_t	-0.189	0.073	**
$\text{FC}_t\text{*Specificity}_i$	-0.078	0.016	***
$\ln(\text{Budget}_t)$	0.697	0.241	**
Exact_i	-0.118	0.082	
Phrase_i	0.004	0.045	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-3 Coefficient Estimates from Cost-per-click Model

	Estimates	Std. Error	
Intercept	-5.662	0.338	***
$\ln(\text{rpc}_{i,t-1})$	2.142	0.115	***
$\ln(\text{Budget}_t)$	0.643	0.035	***
$\ln(\text{QS}_{it})$	-0.587	0.025	***
Google_i	0.195	0.029	***
Brand_i	-1.444	0.172	***
Exact_i	-0.569	0.021	***
Phrase_i	-0.297	0.024	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-4 Coefficient Estimates from Position Model

	Estimates	Std. Error	
Intercept	1.674	0.024	***
$\ln(\text{CPC}_{it})$	-0.693	0.013	***
$\ln(\text{QS}_{it})$	-0.322	0.010	***
Google_i	-0.269	0.008	***
Brand_i	-2.245	0.031	***
Valentine_t	0.088	0.007	***
Mother_t	0.026	0.007	***
Exact_i	-0.161	0.005	***
Phrase_i	-0.005	0.007	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-5 Coefficient Estimates from Click-through-rate Model

	Estimates	Std. Error	
Intercept	-6.270	0.031	***
$\ln(Position_{it})$	-1.263	0.049	***
$\ln(QS_{it})$	1.577	0.014	***
$Specificity_i$	0.030	0.006	***
$Sq(Specificity_i)$	0.009	0.004	*
$Brand_i$	0.906	0.059	***
$Valentine_t$	0.403	0.017	***
$Mother_t$	-0.027	0.014	.
$Exact_i$	1.283	0.009	***
$Phrase_i$	0.661	0.014	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-6 Coefficient Estimates from Conversion Rate Model

	Estimates	Std. Error	
Intercept	-4.583	0.011	***
$\ln(Position_{it})$	0.006	0.015	
$Specificity_i$	-0.003	0.002	
$Sq(Specificity_i)$	0.000	0.001	
$Brand_i$	0.315	0.018	***
$Valentine_t$	0.018	0.005	**
$Mother_t$	0.020	0.004	***
$Exact_i$	0.007	0.003	*
$Phrase_i$	-0.001	0.005	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Appendix B: Examples of the Data

Below Table A-7 is a snippet of the data provided by search engines such as Google regarding the performance of the advertiser's keywords, including the number of impressions, the number of clicks, average cost-per-click (CPC), average position, conversion, revenue (disguised in this example), and quality scores at the keyword level.

Table A-7 Sample Data Observed by the Researcher

Keyword	Match	Day	Search Engine	Impressions	Clicks	CPC	Avg Position	Conversion	Revenue	Quality Score
emerald jewelry	Broad	1/21/2012	Google	2098	34	1.17	1.89	0	0	4
emerald jewelry	Broad	1/22/2012	Google	2220	34	1.12	1.91	0	0	4
emerald jewelry	Broad	1/23/2012	Google	2593	47	1.19	1.91	0	0	4
emerald jewelry	Broad	1/24/2012	Google	2259	36	1.14	2.1	0	0	4
emerald jewelry	Broad	1/25/2012	Google	1889	25	1	2.4	0	0	4
emerald jewelry	Broad	1/26/2012	Google	2168	30	1.2	2.26	0	0	4
emerald jewelry	Broad	1/27/2012	Google	2547	45	1.3	2.01	0	0	4
emerald jewelry	Broad	1/28/2012	Google	2715	47	1.31	1.87	0	0	4
emerald jewelry	Broad	1/29/2012	Google	3954	72	1.19	1.62	1	274.00	4
emerald jewelry	Broad	1/30/2012	Google	3610	67	1.31	1.81	0	0	4

Appendix C: Variation in the Number of Unique Keywords

There is small difference between the numbers of keywords which were clicked under the last-click strategy versus the first-click strategy. More specifically, 6 keywords (e.g. mens claddagh rings, gold emerald rings, etc.) were only clicked under last-click whereas 23 keywords (e.g. alexandrite rings, celtic jewelry for women, etc.) were only clicked under first-click. Most of the keywords clicked only under one attribution strategy were long-tail keywords, which the firm happened to get at a very low cost. The clicking of these unique keywords may or may not be associated with the attribution strategies, as many of them rely on the small chance events that a customer happened to search for a very specific long-tail keyword and happened to click on the focal firm’s search ads. To show that this does not indicate any change in the data generating process of bids, click-throughs and conversions, we have chosen specific time-windows (e.g. 1 month) within the last-click strategy duration and within the first-click strategy duration and shown that such variation in the number of unique keywords clicked in these time-periods are quite typical. (Please see Table A-8 below). Thus, the variation we see across the durations when two different strategies are in play is entirely within the range of changes that happen within similar time-windows when a specific attribution strategy is in play.

Table A-8: Variation in the Number of Unique Keywords Getting Clicked in a Month

Keywords Clicked Only in January	2
Keywords Clicked Only in February	26
Keywords Clicked in Both Months	445

Keywords Clicked Only in February	3
Keywords Clicked Only in March	4
Keywords Clicked in Both Months	468
Keywords Clicked Only in March	0
Keywords Clicked Only in April	10
Keywords Clicked in Both Months	472
Keywords Clicked Only in April	7
Keywords Clicked Only in May	23
Keywords Clicked in Both Months	475
Last-Click Attribution was in use until May 1	
First-Click Attribution was in use since May 2	
Keywords Clicked Only in May	4
Keywords Clicked Only in June	1
Keywords Clicked in Both Months	494
Keywords Clicked Only in June	14
Keywords Clicked Only in July	0
Keywords Clicked in Both Months	481

Appendix D: Robustness Check

1. Censored Data

The change of attribution metrics occurred on May 2, 2012. For all the conversions before this date, the advertiser assigned the conversion revenue using last-click attribution while the conversions on or after May 2, 2012 were assigned to the first clicked keywords. Hence, in the first few days after May 2, 2012, the revenue could be assigned to the first keyword clicked after the change in attribution metric, but not necessarily the first keyword clicked by the customer on his/her purchase journey. That is, some of the purchase paths are left-censored which could result in overestimation of potential revenues. Similarly, towards the end of the data period, the data are also right-censored – some customers were still in the middle of their purchase journeys and thus some revenues have not been realized by the end of the data window. The first-click attribution in this case could underestimate these potential revenues. To address this issue and test the robustness of the proposed model, we drop the first two weeks of data right after the change in attribution metrics and the last two weeks of the data duration. The coefficient estimates for this robustness check are reported below in Table A-9 and Table A-13. The results are close to those reported in Table 3 through Table 7 in the main text, except for the changes in the significant level of the dummy $Mother_t$, which is because Mother's Day was on May 13, 2012, so a large portion of the Mother's Day sales occurred during the two weeks that were excluded in the robustness check. Thus, the dummy variable $Mother_t$ is no longer significant in equation (3) and (5), and becomes significantly negative in equation (4).

Table A-9 Coefficient Estimates from Revenue Model

		Estimates	Std. Error	
α_0	Intercept	-5.359	1.256	***
α_1	$\ln(Impression_{it})$	0.327	0.044	***
α_2	CTR_{it}	0.089	0.013	***
α_3	$CONV_{it}$	0.817	0.252	**
α_4	$Specificity_i$	0.029	0.013	**
α_5	$Sq(Specificity_i)$	0.002	0.009	
α_6	FC_t	-0.136	0.032	***
α_7	$FC_t*Specificity_i$	-0.060	0.016	***
α_8	$\ln(Budget_t)$	0.493	0.112	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-10 Coefficient Estimates from Cost-per-click Model

		Estimates	Std. Error	
β_0	Intercept	-4.985	0.519	***
β_1	$\ln(rpc_{i,t-1})$	3.471	0.280	***
β_2	$\ln(Budget_t)$	0.542	0.052	***
β_3	$\ln(QS_{it})$	-0.831	0.049	***
β_4	$Google_i$	0.002	0.038	
β_5	$Brand_i$	-3.060	0.297	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-11 Coefficient Estimates from Position Model

		Estimates	Std. Error	
θ_0	Intercept	1.836	0.025	***
θ_1	$\ln(CPC_{it})$	-0.593	0.012	***
θ_2	$\ln(QS_{it})$	-0.384	0.011	***
θ_3	$Google_i$	-0.432	0.008	***
θ_4	$Brand_i$	-1.993	0.031	***
θ_5	$Valentine_t$	0.097	0.007	***
θ_6	$Mother_t$	-0.017	0.017	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-12 Coefficient Estimates from Click-through-rate Model

		Estimates	Std. Error	
μ_0	Intercept	-5.034	0.044	***
μ_1	$\ln(\text{Position}_{it})$	-2.367	0.067	***
μ_2	$\ln(\text{QS}_{it})$	1.644	0.021	***
μ_3	Specificity_i	-0.182	0.009	***
μ_4	$\text{Sq}(\text{Specificity}_i)$	-0.044	0.005	***
μ_5	Brand_i	0.202	0.186	
μ_6	Valentine_t	0.597	0.024	***
μ_7	Mother_t	-0.137	0.050	**

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-13 Coefficient Estimates from Conversion Rate Model

		Estimates	Std. Error	
ϕ_0	Intercept	-4.573	0.010	***
ϕ_1	$\ln(\text{Position}_{it})$	-0.005	0.014	
ϕ_2	Specificity_i	-0.003	0.002	.
ϕ_3	$\text{Sq}(\text{Specificity}_i)$	0.000	0.001	
ϕ_4	Brand_i	0.290	0.018	***
ϕ_5	Valentine_t	0.023	0.005	***
ϕ_6	Mother_t	0.008	0.009	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

2. Regression Discontinuity

Regression discontinuity assigns a threshold for the experimental treatment. By comparing observations lying closely on either side of the threshold, the local average treatment effect can be estimated. In our context, we do not assign such a threshold to the keywords. The advertiser uses the same bidding strategy through the entire data window. However, by using a procedure similar to regression discontinuity, we can better analyze the localized impact immediately before and after the change of attribution metrics and remove the possible time-related impact such as seasonality and other noises.

In the proposed model, two holidays are captured – Valentine's Day and Mother's Day. Since the attribution metric was changed on May 2, 2012, a short window around this date does not cover Valentine's Day. Thus, we have to remove the dummy variable $Valentine_t$, the value of which in the localized analysis will always be 0. Table A-14 shows the coefficient estimates for ± 1 week, ± 2 weeks, up to ± 4 weeks of data around the date of attribution switch. Applying regression discontinuity to these four subsets of data provides us the coefficient estimates which closely resemble the estimates based on the entire dataset, while some of the estimates are less significant due to fewer observations. With ± 1 week of data, the coefficient of FC_t is negative and its p-value is 0.194. Its p-value is reduced to 0.081 with ± 2 weeks of data, to 0.137 with ± 3 weeks of data and to 0.046 with ± 4 weeks of data. However, $FC_t*Specificity_i$ is negative and significant from ± 2 weeks onwards. Overall, this indicates that first-click does impact overall revenues negatively even in the localized analysis. We believe that the reason that the significance is not observed in the ± 1 week of data is because the bidding algorithm still incorporates some of the historical data from the last-click condition and it takes a few days for the last-click effect to completely wash out in the bidding procedure. Given that the event change is exogenous, these results with the focus on much shorter time windows eliminate other time-dependent factors as possible reasons for the change in revenue. Thus, our results seem quite robust and indicate that the change in revenue is clearly due to the attribution change.

Table A-14 Coefficient Estimates for Regression Discontinuity

	± 1 week		± 2 weeks		± 3 weeks		± 4 weeks	
eqn(1)	Estimate		Estimate		Estimate		Estimate	
Intercept	-2.438		-1.484		-2.414	*	-3.953	.
$\ln(Impression_{it})$	0.367	***	0.397	***	0.322	***	0.296	***
CTR_{it}	0.091	***	0.102	***	0.080	***	0.071	***
$CONV_{it}$	0.273		0.030		0.375	*	0.738	*
$Specificity_i$	0.021		-0.005		0.020		0.020	
$Sq(Specificity_i)$	0.001		-0.008		-0.003		0.008	
$First\text{-}Click_t$	-0.003		-0.037	.	-0.005		-0.072	*
$First\text{-}Click_t*Specificity_i$	-0.015		-0.035	*	-0.051	***	-0.048	**
$\ln(Budget_t)$	0.214		0.120		0.231	*	0.371	.
eqn(2)								
Intercept	-4.531		6.688		6.072	*	4.079	**
$\ln(rpc_{i,t-1})$	4.228	**	3.851	***	2.923	***	3.977	***
$\ln(Budget_t)$	0.490		-0.716		-0.608	*	-0.435	*
$\ln(QS_{it})$	-0.973	***	-0.864	***	-0.821	***	-0.895	***
$Google_i$	-0.083		-0.103		-0.186	*	-0.113	
$Brand_i$	-5.600		-9.861	***	-7.908	***	-8.146	***
eqn(3)								

Intercept	1.573	***	1.743	***	1.682	***	1.657	***
$\ln(CPC_{it})$	-0.633	***	-0.686	***	-0.670	***	-0.613	***
$\ln(QS_{it})$	-0.288	***	-0.349	***	-0.332	***	-0.323	***
$Google_i$	-0.330	***	-0.381	***	-0.328	***	-0.331	***
$Brand_i$	-1.992	***	-2.139	***	-2.134	***	-2.032	***
$Mother_t$	0.034	*	0.035	***	0.016	*	0.015	*

eqn(4)

Intercept	-1.638	*	-2.402	***	-1.231	*	-2.634	***
$\ln(Position_{it})$	-11.092	***	-8.715	***	-11.028	***	-8.028	***
$\ln(QS_{it})$	3.200	***	2.732	***	2.984	***	2.493	***
$Specificity_i$	-1.228	***	-1.003	***	-1.217	***	-0.820	***
$Sq(Specificity_i)$	-0.190	***	-0.119	***	-0.102	***	-0.089	***
$Brand_i$	-7.449	***	-6.032	***	-8.485	***	-5.261	***
$Mother_t$	-0.080		0.007		0.007		0.114	.

eqn(5)

Intercept	-4.515	***	-4.549	***	-4.533	***	-4.547	***
$\ln(Position_{it})$	-0.077		-0.034		-0.056		-0.038	
$Specificity_i$	-0.023	*	-0.011		-0.010	.	-0.007	
$Sq(Specificity_i)$	-0.002		-0.002		-0.002		-0.002	
$Brand_i$	0.467	***	0.424	***	0.353	***	0.337	***
$Mother_t$	0.013		0.017	*	0.018	**	0.021	***

3. Fixed Effects

We also test the proposed model with keyword-level fixed effects in equation (1). Table A-15 shows the results for equation (1) through (5) while adding the keyword-level fixed effects and omitting the intercept in equation (1). Due to limited space, we do not report the estimates of the fixed effects here. In equation (1), all the coefficients have the same signs as those in Table 4, but the value of $Specificity_i$ is much larger in the fixed effects model. Additionally, the coefficient of $Specificity_i^2$ becomes significant. These two variables together reveal a U-shaped relationship between the revenue and the keyword specificity, with the turning point at -1.761. Given that all keywords are on the right side of the turning point, the relationship between the revenue and the keyword specificity in equation (1) of the fixed effects model is still monotonically increasing, the same as the relationship found in Table 4 in the main text. In equations (2) – (5), some coefficients become more significant in the fixed effects model due to more instrumental variables served by the fixed effects dummies. Overall, the fixed effects model replicates the findings in the main text.

Table A-15 Coefficient Estimates with Fixed Effects

eqn(1)	Estimate	Std. Error	
Intercept	–	–	
$\ln(Impression_{it})$	0.861	0.124	***
CTR_{it}	0.047	0.013	***
$CONV_{it}$	1.264	0.302	***
$Specificity_i$	14.452	4.843	***
$Sq(Specificity_i)$	4.104	1.593	***
$First\text{-}Click_t$	-0.510	0.149	***
$First\text{-}Click_t * Specificity_i$	-0.085	0.018	***
$\ln(Budget_t)$	1.463	0.457	***

eqn(2)			
Intercept	-4.080	0.128	***
$\ln(rpc_{i,t-1})$	0.185	0.011	***
$\ln(Budget_t)$	0.569	0.014	***
$\ln(QS_{it})$	-0.538	0.009	***
$Google_i$	-0.188	0.009	***
$Brand_i$	-0.023	0.061	

eqn(3)			
Intercept	1.326	0.017	***
$\ln(CPC_{it})$	-0.432	0.004	***
$\ln(QS_{it})$	-0.199	0.007	***
$Google_i$	-0.247	0.007	***
$Brand_i$	-1.676	0.014	***
$Valentine_t$	0.123	0.007	***
$Mother_t$	0.019	0.006	***

eqn(4)			
Intercept	-5.825	0.023	***
$\ln(Position_{it})$	-0.634	0.011	***
$\ln(QS_{it})$	1.397	0.014	***
$Specificity_i$	-0.036	0.005	***

$Sq(Specificity_i)$	-0.030	0.004	***
$Brand_i$	1.853	0.043	***
$Valentine_t$	0.280	0.016	***
$Mother_t$	-0.040	0.015	***
eqn(5)			
Intercept	-4.554	0.003	***
$\ln(Position_{it})$	-0.033	0.003	***
$Specificity_i$	-0.006	0.002	***
$Sq(Specificity_i)$	0.000	0.001	
$Brand_i$	0.287	0.013	***
$Valentine_t$	0.024	0.005	***
$Mother_t$	0.024	0.005	***

Appendix E: Alternative Measures of the Keyword Specificity

In the main text, we measure the keyword specificity with the judge ratings of a keyword. Next, we present the estimation results using the number of characters contained in a keyword and the number of words contained in a keyword, respectively, as the measure of specificity.

1. Using the number of characters in a keyword as the specificity measure

First, we measure the keyword specificity with the number of characters in a keyword. Each keyword contains 7 to 43 characters, with the average at 19.82 and the median at 19. Table A-16 shows the coefficient estimates of equation (1). Compared with Table 3, $Specificity_i^2$ turns positive and significant but in negligible magnitude, while the rest of the coefficients are all significant and have the same signs as those in Table 3. The revenue demonstrates a very flat U-curve with respect to the keyword specificity and the turning point is at -24.086. Given that the value of $Specificity_i$ is in the range [7, 43], the revenue is monotonically increasing with more specific keywords, the same as our finding in the main text.

At the mean specificity, i.e. 19.82 characters, $\alpha_6 FC_t + \alpha_7 FC_t * Specificity_i = -0.150$. The overall impact of first-click metric on keyword campaign is still negative. The coefficient estimates for equation (2)- (5) are very close to those in Table 4-7, with only two exceptions in equation (4): the coefficient of $Specificity_i$ turns to be positive, but it does not change the inverted-U relationship between the click-through rate and keyword specificity and the coefficient of $Brand_i$ becomes positive and significant, revealing the fact that branded keywords lead to higher click-through rate which we do not find when using judge ratings to measure the keyword specificity.

Table A-16 Coefficient Estimates from Revenue Model (Specificity measure is the number of characters)

		Estimates	Std. Error	
α_0	Intercept	-5.139	1.338	***
α_1	$\ln(\text{Impression}_{it})$	0.258	0.049	***
α_2	CTR_{it}	0.080	0.011	***
α_3	CONV_{it}	0.949	0.249	***
α_4	Specificity_i	-0.068	0.019	***
α_5	$\text{Sq}(\text{Specificity}_i)$	0.001	0.000	***
α_6	FC_t	-0.068	0.058	***
α_7	$\text{FC}_t\text{*Specificity}_i$	-0.004	0.002	*
α_8	$\ln(\text{Budget}_t)$	0.579	0.143	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-17 Coefficient Estimates from Cost-per-click Model (Specificity measure is the number of characters)

		Estimates	Std. Error	
β_0	Intercept	-6.724	0.775	***
β_1	$\ln(\text{rpc}_{i,t-1})$	4.553	0.469	***
β_2	$\ln(\text{Budget}_t)$	0.690	0.077	***
β_3	$\ln(\text{QS}_{it})$	-0.926	0.070	***
β_4	Google_i	0.047	0.052	
β_5	Brand_i	-3.541	0.461	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-18 Coefficient Estimates from Position Model (Specificity measure is the number of characters)

		Estimates	Std. Error	
θ_0	Intercept	1.746	0.022	***
θ_1	$\ln(\text{CPC}_{it})$	-0.513	0.010	***
θ_2	$\ln(\text{QS}_{it})$	-0.345	0.009	***
θ_3	Google_i	-0.429	0.008	***
θ_4	Brand_i	-1.790	0.026	***
θ_5	Valentine_t	0.109	0.007	***
θ_6	Mother_t	0.022	0.006	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-19 Coefficient Estimates from Click-through-rate Model (Specificity measure is the number of characters)

		Estimates	Std. Error	
μ_0	Intercept	-6.226	0.070	***
μ_1	ln($Position_{it}$)	-2.069	0.068	***
μ_2	ln(QS_{it})	1.507	0.021	***
μ_3	$Specificity_i$	0.122	0.004	***
μ_4	Sq($Specificity_i$)	-0.003	0.000	***
μ_5	$Brand_i$	0.975	0.074	***
μ_6	$Valentine_t$	0.558	0.023	***
μ_7	$Mother_t$	-0.026	0.018	

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

Table A-20 Coefficient Estimates from Conversion Rate Model (Specificity measure is the number of characters)

		Estimates	Std. Error	
ϕ_0	Intercept	-4.567	0.018	***
ϕ_1	ln($Position_{it}$)	-0.021	0.014	
ϕ_2	$Specificity_i$	0.001	0.001	
ϕ_3	Sq($Specificity_i$)	0.000	0.000	
ϕ_4	$Brand_i$	0.307	0.014	***
ϕ_5	$Valentine_t$	0.023	0.005	***
ϕ_6	$Mother_t$	0.021	0.004	***

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

In Table A-21, we calculate the change in revenue when the advertiser switches from the last-click to the first-click attribution. According to the coefficient estimates of equation (1), the change in log-revenue of keyword *i* is $\Delta_i=\alpha_6 FC_t + \alpha_7 FC_t * Specificity_i$. The 2nd column of Table A-21 shows the summary statistics of the judge ratings of a keyword. The 3rd column shows the Δ values accordingly. Moreover, the 4th column shows the summary statistics of the number of characters in a keyword, whereas the corresponding Δ values are presented in the 5th column. The magnitude of the Δ values in the 3rd column is about twice of those in the 5th column, but two different measures of keyword specificity both reveal the same negative impact of the first-click attribution metric, compared with the last-click metric, on the entire search campaign revenue. Column 6 and 7 in Table A-21 will be discussed in the next subsection.

Table A-21 Changes in Log-revenue Due to the Change of Attribution Metrics

	Judge Ratings	Δ	Number of Characters	Δ	Number of Words	Δ
Minimum	1	-0.228	7	-0.097	1	-0.130
1st Quartile	2	-0.298	14	-0.126	2	-0.157
Median	2	-0.298	19	-0.147	3	-0.184
Mean	2.383	-0.324	19.82	-0.150	2.869	-0.180
3rd Quartile	3	-0.367	24	-0.168	3	-0.184
Maximum	5	-0.507	43	-0.246	6	-0.265

2. Using the number of words in a keyword as the specificity measure

Next, we use the number of words as the measure of the keyword specificity. Each keyword in the data set contains 1 to 6 words, with 2.869 words on average and the median is 3 words. Table A-22 shows the coefficient estimates for equation (1) when the specificity measure is the number of words contained in a keyword. Again, there is a significant but flat U curve for the revenue against the keyword specificity, with the turning point at -3.686 smaller than all possible values of $Specificity_i$. It indicates the relationship between revenue and keyword specificity is monotonically increasing, the same as our finding in the main text. The coefficient estimates for equation (2) to (5) are shown in Table A-23 to Table A-26 in which all the estimation results are close to the results in Table 4 to Table 7. The summary statistics of the number of words is in the 6^{th} column of Table A-21 and the changes in revenue when switching attribution metrics are in the 7^{th} column. At the mean leave, the revenue implication of attribution change is -0.180, which is again negative and in the same range of our findings when using the number of characters as the keyword specificity measure.

Table A-22 Coefficient Estimates from Revenue Model (Specificity measure is the number of words)

		Estimates	Std. Error	
α_0	Intercept	-5.820	1.370	***
α_1	$\ln(Impression_{it})$	0.268	0.052	***
α_2	CTR_{it}	0.084	0.011	***
α_3	$CONV_{it}$	1.011	0.257	***
α_4	$Specificity_i$	0.528	0.188	**
α_5	$Sq(Specificity_i)$	0.072	0.026	**
α_6	FC_t	-0.103	0.058	**
α_7	$FC_t*Specificity_i$	-0.027	0.013	*
α_8	$\ln(Budget_t)$	0.654	0.154	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-23 Coefficient Estimates from Cost-per-click Model (Specificity measure is the number of words)

		Estimates	Std. Error	
β_0	Intercept	-4.974	0.381	***
β_1	$\ln(rpc_{i,t-1})$	2.397	0.177	***
β_2	$\ln(Budget_t)$	0.575	0.039	***
β_3	$\ln(QS_{it})$	-0.712	0.032	***
β_4	$Google_i$	-0.031	0.026	
β_5	$Brand_i$	-2.060	0.207	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-24 Coefficient Estimates from Position Model (Specificity measure is the number of words)

		Estimates	Std. Error	
θ_0	Intercept	1.879	0.026	***
θ_1	$\ln(CPC_{it})$	-0.630	0.014	***
θ_2	$\ln(QS_{it})$	-0.400	0.011	***
θ_3	$Google_i$	-0.442	0.008	***
θ_4	$Brand_i$	-2.065	0.033	***
θ_5	$Valentine_t$	0.096	0.007	***
θ_6	$Mother_t$	0.026	0.007	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-25 Coefficient Estimates from Click-through-rate Model (Specificity measure is the number of words)

		Estimates	Std. Error	
μ_0	Intercept	-6.546	0.076	***
μ_1	$\ln(Position_{it})$	-2.008	0.069	***
μ_2	$\ln(QS_{it})$	1.493	0.020	***
μ_3	$Specificity_i$	1.019	0.034	***
μ_4	$Sq(Specificity_i)$	-0.164	0.005	***
μ_5	$Brand_i$	1.207	0.077	***
μ_6	$Valentine_t$	0.539	0.023	***
μ_7	$Mother_t$	-0.030	0.018	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-26 Coefficient Estimates from Conversion Rate Model (Specificity measure is the number of words)

		Estimates	Std. Error	
ϕ_0	Intercept	-4.578	0.019	***
ϕ_1	$\ln(\text{Position}_{it})$	-0.018	0.014	
ϕ_2	Specificity_i	0.012	0.008	
ϕ_3	$\text{Sq}(\text{Specificity}_i)$	-0.002	0.001	.
ϕ_4	Brand_i	0.313	0.015	***
ϕ_5	Valentine_t	0.022	0.005	***
ϕ_6	Mother_t	0.022	0.004	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

In summary, we estimate equation (1) to (5) with two alternative specificity measures – the number of characters in a keyword and the number of words in a keyword. Using these two alternative specificity measures, we are also able to find the positive relationship between the keyword specificity and the revenue in equation (1) as we find when using judge ratings as the measure. In addition, we find a significant inverted-U shape of the click-through rates with respect to the keyword specificity with both alternative measures. The impact of keyword specificity on the conversion rate is not significant at the 5% level with either measure.

Appendix F: The General Nature of the Bidding Algorithm

The bidding algorithm solves a relaxation to the multiple-choice knapsack problem. The optimal solution to the knapsack relaxation can be obtained by ordering each keyword-bid level combination in terms of expected marginal ROI from highest to lowest. The algorithm starts picking from the top in order of decreasing marginal ROI such that each keyword is picked only once till the total expected costs is just under or equal to the available budget constraint. It can be shown that this method maximizes the expected revenue and is an optimal strategy (Pani 2010). Although the firm uses a different method to solve the knapsack relaxation, the optimal bids determined by the firm's algorithm would be identical to that obtained by the method above. When the firm changes its attribution strategy from last-click to first-click, the expected revenues at different bid levels change and thus the ordering of the keywords based on their expected ROI changes. This changes the bid levels for keywords. We illustrate this ordering of the keywords chosen under each strategy as shown in Figure A-1 below using a hypothetical set of 11 keywords.

Figure A-1: The Ordering of Keywords under Different Attribution Strategies

ROI	Last-Click Attribution	First-Click Attribution
Highest	K1	K10
	K2	K9
	K3	K7
	K4	K8
	K5	K5
	K6	K6
	K7	K4
	K8	K3
	K9	K2
	K10	K11
Lowest	K11	K1

Here the same budget is allocated under each strategy, but under the last-click strategy based on the expected ROI for each keyword-bid combination, we are able to bid on a total of 9 keywords while under the first-click strategy we are able to bid on 10 keywords with the same available budget. **The resulting reordering under the strategy change and the resulting change in the mix of keywords chosen are what cause the changes in the overall revenue the firm makes under each strategy.**

Next, we provide more information regarding the general nature of our bidding algorithm. The bidding algorithm we use is quite typical of the algorithms that are used in the industry. At its core, there are two alternative optimization approaches that are used in the industry (these are also explained in details in the two academic papers we cite below:

1) Absolute ROI equalization approach: involves calculating the expected absolute ROI (expected revenue to expected cost ratio) for each keyword and finding the bid across these keywords that *equalizes the absolute expected ROI* across these keywords while adhering to budget constraints. The different players in industry use various heuristics to do this, the core idea of these heuristics is ordering of keywords outlined above.

2) The Knapsack variant approach: where *keywords and their associated bids are selected* based on the ROI (expected revenue over expected cost ratio) of keyword-bid combinations so as to maximize revenue under the budget constraint (Borgs et al. 2007; Rusmevichientong and Williamson 2006). This approach is also called the portfolio optimization approach and different variants of this approach are used by our focal ad agency as well as by agencies such as Kenshoo and Marin Software.

Regardless of the bidding approach used, it is easy to see that attribution strategy plays a central role in attributing the ***expected revenue for keywords*** and therefore plays a critical role in how the ROI is determined for the keywords, which ultimately determines the keywords and their associated bids.

Reference:

Borgs, C., Chayes, J., Immorlica, N., Jain, K., Etesami, O., & Mahdian, M. (2007). Dynamics of bid optimization in online advertisement auctions. In *Proceedings of the 16th international conference on World Wide Web* (pp. 531-540). ACM.

Pani, A. (2010). Models for budget constrained auctions: an application to sponsored search and other auctions. Ph.D. thesis. University of Maryland.

Rusmevichientong, P., & Williamson, D. P. (2006). An adaptive algorithm for selecting profitable keywords for search-based advertising services. In *Proceedings of the 7th ACM Conference on Electronic Commerce* (pp. 260-269). ACM.

Appendix G: Data Generating Process

There could be a concern that, as the revenue is affected by the attribution strategy, the bidding process will also be influenced by the attribution strategy. In other words, while there is a dummy variable to represent the attribution strategy in use in equation (1) in the main text, should equation (2) also include an explicit variable to control the attribution strategy? In this section, we will examine the data generating process (DGP) and answer this question.

In Figure A-1, we find in the new ordering under first-click strategy, keywords K5 and K6 retain their original positions in the order and may end up with similar bids under both strategies. We use this idea to test whether the DGP for the customers' click-throughs and conversions remain the same under the two strategies.

We identify those keywords in our dataset which have similar positions (the difference between the average positions before and after the attribution change is no more than 0.05) and compare their average click-throughs and average conversions under each strategy. We have found 55 such keywords and the results tabulated below in Table A-27 show that these averages are nearly identical and the DGP has not changed. In Figures A-2 – A-4, we present the distribution of the average CPC, click-through rate and conversion rate of these 55 keywords under both Last-Click and First-Click. We also conducted t-tests for each keyword under the two strategies and we could not reject the null hypothesis of no difference in average CPC (in 86% of the cases, p-value>0.05), average click-through rates (in 81% of the cases, p-value>0.05), and conversions (in 78% of the cases, p-value>0.05). In addition, as shown in Table A-27, in testing for the differences in averages for keywords across the two strategies, using a matched sample t test, the null hypothesis of no difference in averages is retained for all the metrics - CPC, CTR and conversion rate.

Table A-27: the Changes from Last-Click to First-Click Based on 55 Keywords

	Difference in the Means	p-value (H_0: the DGP is the same before and after the change)
Average Changes in CPC	$0.06241	0.349
Average Changes in CTR	-0.00031	0.441
Average Changes in Conversion Rate	-0.00056	0.409

Figure A-2: The Distribution of Average CPC Based on 55 Keywords

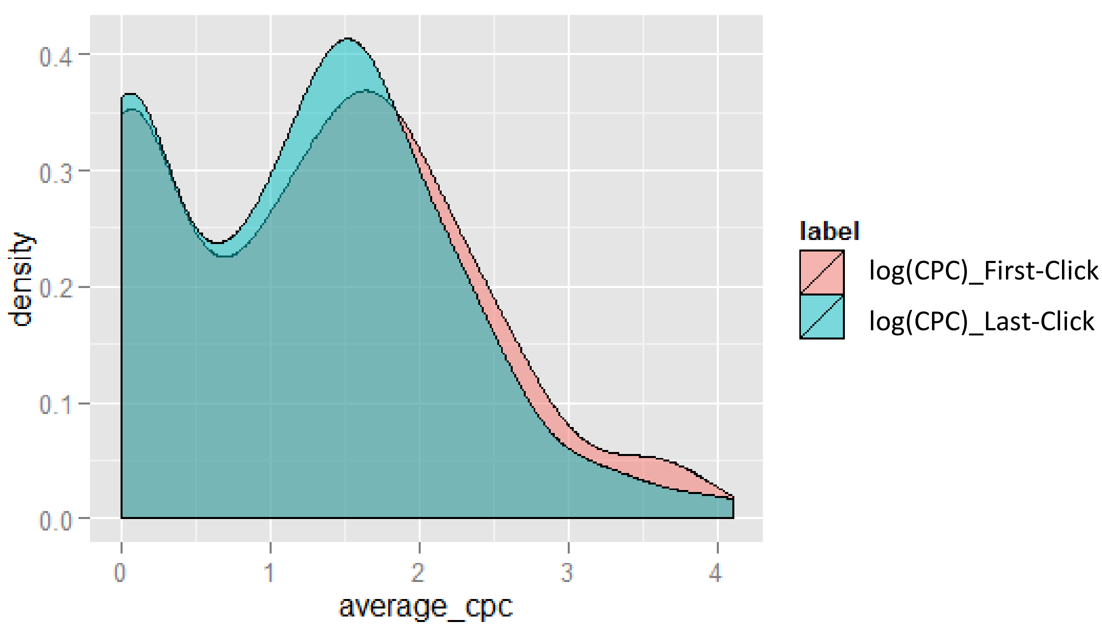


Figure A-3: The Distribution of Average Click-through-rate Based on 55 Keywords

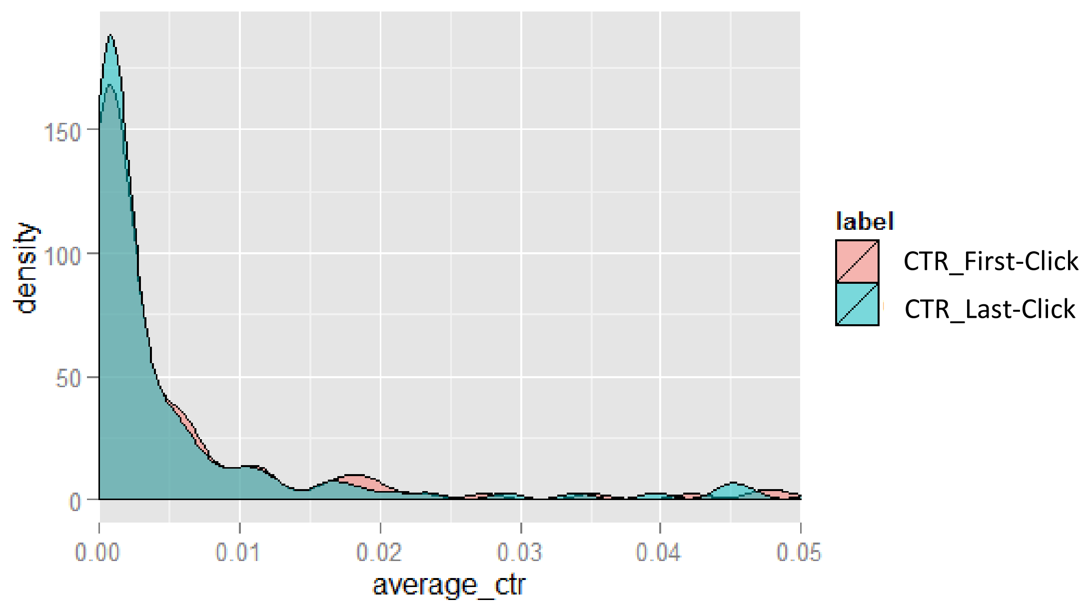
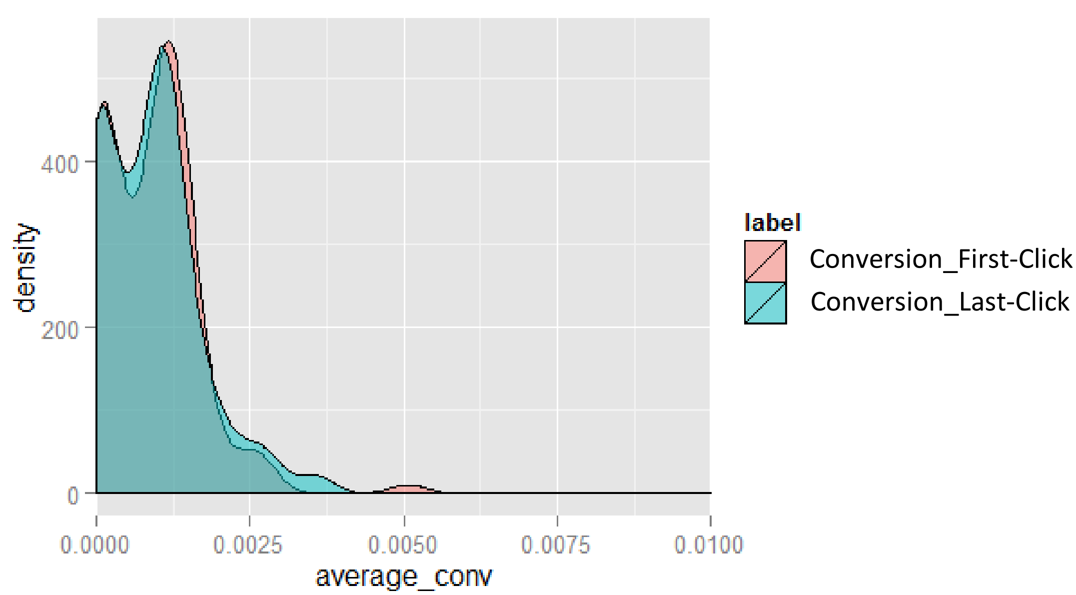


Figure A-4: The Distribution of Average Conversion-rate Based on 55 Keywords



Appendix H: Model Predictions

Next, we compare the predictive validity of the proposed model with Ghose and Yang's model (2009). There are two important differences between the proposed model and Ghose and Yang's model (GY Model): first, the revenue is not observed and, thus, not modeled in the GY model; second, the bidding decision is made based on the lagged position of a keyword in the GY model, while in the proposed model, the bidding decision depends on the lagged revenue-per-click (reflecting the focal advertiser's practice), so that the bidding decision (equation (2)) is linked with the revenue generation (equation (1)). In the following comparison, we reflect these differences in the modeling, but do not use exactly the same variables as in the GY model. For example, the GY model uses separate dummies for retailer and brand name, while these two are the same in our context. Moreover, we estimate both the proposed model and GY model with 3SLS to make them comparable, although Ghose and Yang (2009) estimate their model with Seemingly Unrelated Regression (SUR).

The mean absolute error (MAE) of the proposed model is 0.372, 1.170, and 0.065 for equation (3), (4), and (5), all of which are smaller than GY model (the MAE is 0.764, 4.408 and 0.068, respectively). This implies better prediction of ad position, click-through rate, and conversion rate by the proposed model. The MAE for equation (2) by the proposed model is 1.478 which is also very close to that of GY model which is 1.387. In addition, we compare the MAE of the proposed model with a model without supply side information, i.e. equation (1) and (2) are not included. We find the proposed model also outperforms a demand-side-only model in each equation in the system. In general, explicitly modeling the revenue generation and the bidding decision helps improve the predictive validity in the proposed model.

Reference:

Ghose A, Yang S (2009) An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Sci.* 55(10):1605–1622.

Appendix I：Simulated Policy as a Linear Combination of Last-Click and First-Click

Along a customer's purchase funnel with multiple keyword clicks, a keyword can be clicked as the first keyword, middle keywords, or the last keyword. For the first keyword, its performance is the best under the first-click strategy, worst under the last-click strategy and in-between under the weighted-linear attribution we propose in the policy simulation in the main text. On the other hand, the last keyword performs the best under the last-click strategy, worst under the first-click strategy and in-between under the weighted-linear strategy. The performance of middle keywords under the linear strategy should be no worse than its performance under either first-click or last-click. Thus, when we assume the performance of middle keywords in the simulation is a linear combination of its weaker performances under first-click and last-click, it is a conservative assumption and provides a lower bound for its performance if the focal firm were using a fractional attribution strategy considering the position of all keywords in the funnel. In an optimal setting, the middle keywords can gain higher level of revenue which we cannot estimate due to the lack of individual level data.

We show empirically below for each keyword, their revenues are monotonically non-decreasing with better ad position (Figure A-5, the smaller value represents a better position). Since the ad positions for a keyword under a linear combination of first-click and last-click strategy is likely to be in-between their extreme ad-positions under first-click or last-click as shown in Figure A-6 (as bidding amount will be in-between the bids under first-click or under last-click), we can argue that the revenue will be in-between the revenues under first-click or last-click. Thus, we can use the convex combination to estimate for revenues under an attribution metric in-between first-click and last-click.

Figure A-5: The Average Daily Revenue for Each Ad Position

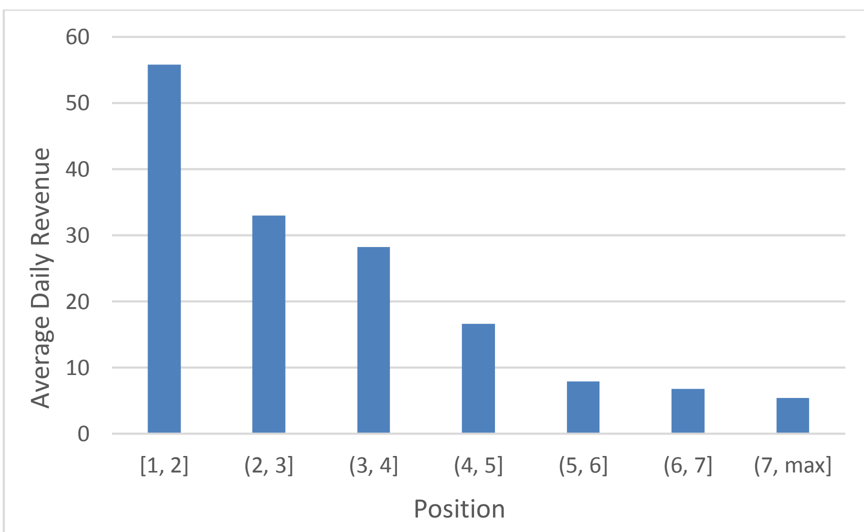


Figure A-6: The Average Ad Position at Different Specificity